

A Type of Shannon-McMillan Approximation Theorems for Second-Order Nonhomogeneous Markov Chains Indexed by a Double Rooted Tree

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Abstract. In this paper, a class of small deviation theorems for the relative entropy densities of arbitrary random field on a double rooted tree are discussed by comparing between the arbitrary measure μ and the second-order nonhomogeneous Markov measure μ_Q on the double rooted tree. As corollaries, some Shannon-McMillan theorems for the arbitrary random field, second-order Markov chain field and a limit property for the random conditional entropy of second-order homogeneous Markov chain on the double rooted tree are obtained. The existing result is extended.

Key Words and Phrases: Shannon-McMillan theorem, a double rooted tree, arbitrary random field, second-order nonhomogeneous Markov chain, relative entropy density.

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1. Introduction

A tree is a graph $S = \{T, E\}$ which is connected and contains no circuits. Given any two vertices σ, t ($\sigma \neq t \in T$), let $\overline{\sigma t}$ be the unique path connecting σ and t . Define the graph distance $d(\sigma, t)$ to be the number of edges contained in the path $\overline{\sigma t}$.

Let T_o be an arbitrary infinite tree that is partially finite (i.e. it has infinite vertices, and each vertex connects with finite vertices) and has a root o . Meanwhile, we consider another kind of double root tree T , that is, it is formed with the root o of T_o connecting with an arbitrary point denoted by the root -1 . For a better explanation of the double root tree T , we take Cayley tree $T_{C,N}$ for example. It's a special case of the tree T_o , the root o of Cayley tree has N neighbors and all the other vertices of it have $N + 1$ neighbors each. The double root tree $T'_{C,N}$ (see Fig.1) is formed with root o of tree $T_{C,N}$ connecting with another root -1 .

Let σ, t be vertices of the double root tree T . Write $t \leq \sigma$ ($\sigma, t \neq o, -1$) if t is on the unique path connecting o to σ , and $|\sigma|$ for the number of edges on this path. For any

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two vertices σ, t ($\sigma, t \neq o, -1$) of the tree T , denote by $\sigma \wedge t$ the vertex farthest from o satisfying $\sigma \wedge t \leq \sigma$ and $\sigma \wedge t \leq t$.

The set of all vertices with distance n from root o is called the n -th generation of T , which is denoted by L_n . We say that L_n is the set of all vertices on level n and especially root -1 is on the -1 st level on tree T . We denote by $T^{(n)}$ the subtree of the tree T containing the vertices from level -1 (the root -1) to level n and denote by $T_o^{(n)}$ the subtree of the tree T_o containing the vertices from level 0 (the root o) to level n . Let $t (\neq o, -1)$ be a vertex of the tree T . We denote the first predecessor of t by 1_t , the second predecessor of t by 2_t , and denote by n_t the n -th predecessor of t . Let $X^A = \{X_t, t \in A\}$, and let x^A be a realization of X^A and denote by $|A|$ the number of vertices of A .

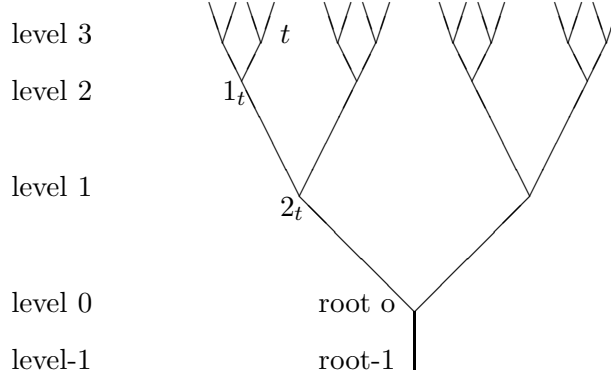


Fig.1 Double root tree $T'_{C,2}$

Definition 1 Let $S = \{s_1, s_2, \dots, s_M\}$ and $Q(z|y, x)$ be a nonnegative function on S^3 . Let

$$Q = ((Q(z|y, x)), \quad Q(z|y, x) \geq 0, \quad x, y, z \in S.$$

If

$$\sum_{z \in S} Q(z|y, x) = 1,$$

then Q is called a second-order transition matrix.

Definition 2 Let T be a double root tree and $S = \{s_1, s_2, \dots, s_M\}$ be a finite state space, and $\{X_t, t \in T\}$ be a collection of S -valued random variables defined on the probability space (Ω, \mathcal{F}, Q) . Let

$$q = (q(x, y)), \quad x, y \in S \tag{1}$$

be a distribution on S^2 , and

$$Q_t = (Q_t(z|y, x)), \quad x, y, z \in S, \quad t \in T \setminus \{o\} \setminus \{-1\} \tag{2}$$

be a collection of second-order transition matrices. For any vertex t ($t \neq o, -1$), if

$$\begin{aligned} & Q(X_t = z | X_{1_t} = y, X_{2_t} = x, \text{ and } X_\sigma \text{ for } \sigma \wedge t \leq 2_t) \\ & = Q(X_t = z | X_{1_t} = y, X_{2_t} = x) = Q_t(z | y, x) \quad \forall x, y, z \in S \end{aligned} \quad (3)$$

and

$$Q(X_{-1} = x, X_o = y) = q(x, y), \quad x, y \in S, \quad (4)$$

then $\{X_t, t \in T\}$ is called a S -valued second-order nonhomogeneous Markov chain indexed by a tree T with the initial distribution (1) and second-order transition matrices (2), or called a T -indexed second-order nonhomogeneous Markov chain.

Definition 3. Let $(Q_t = Q_t(z | x, y), t \in T^{(n)} \setminus \{o, -1\})$ and $q = (q(x, y))$ be defined as before, μ_Q be a second-order nonhomogeneous Markov measure on (Ω, \mathcal{F}) . If

$$\mu_Q(x_0, x_{-1}) = q(x_0, x_{-1}) \quad (5)$$

$$\mu_Q(x^{T^{(n)}}) = q(x_0, x_{-1}) \prod_{t \in T^{(n)} \setminus \{o, -1\}} Q_t(x_t | x_{1_t}, x_{2_t}), \quad n \geq 1, \quad (6)$$

then μ_Q will be called a second-order Markov chains field on an infinite tree T determined by the stochastic matrices Q_t and the initial distribution q .

Let μ be an arbitrary probability measure defined on (Ω, \mathcal{F}) , \log is the natural logarithmic. Denote

$$f_n(\omega) = -\frac{1}{|T^{(n)}|} \log \mu(X^{T^{(n)}}). \quad (7)$$

$f_n(\omega)$ is called the entropy density on subgraph $T^{(n)}$ with respect to the measure μ . If $\mu = \mu_Q$, then by (6), (7) we get

$$f_n(\omega) = -\frac{1}{|T^{(n)}|} [\log q(X_0, X_{-1}) + \sum_{t \in T^{(n)} \setminus \{o, -1\}} Q_t(X_t | X_{1_t}, X_{2_t})]. \quad (8)$$

The convergence of $f_n(\omega)$ in a sense (L_1 convergence, convergence in probability, or almost sure convergence) is called Shannon-McMillan theorem or the asymptotic equipartition property (AEP) in information theory. There have been some works on limit theorems for tree-indexed stochastic processes. Benjamini and Peres [1] have given the notion of the tree-indexed Markov chains and studied the recurrence and ray-recurrence for them. Berger and Ye [2] have studied the existence of entropy rate for some stationary random fields on a homogeneous tree. Ye and Berger (see [4],[5]), by using Pemantle's result [3] and a combinatorial approach, have studied the Shannon-McMillan theorem with convergence in probability for a PPS-invariant and ergodic random field on a homogeneous tree. Yang and Liu [8] have studied a strong law of large numbers for the frequency of occurrence of states for Markov chains field on a homogeneous tree (a particular case of tree-indexed Markov chains field and PPS-invariant random fields). Yang (see [6]) has studied the

strong law of large numbers for frequency of occurrence of state and Shannon-McMillan theorem for homogeneous Markov chains indexed by a homogeneous tree. Recently, Yang (see [13]) has studied the strong law of large numbers and Shannon-McMillan theorem for nonhomogeneous Markov chains indexed by a homogeneous tree. Huang and Yang (see [11]) have also studied the strong law of large numbers for Markov chains indexed by an infinite tree with uniformly bounded degree. Peng and Yang have studied a class of small deviation theorems for functionals for arbitrary random field on a homogeneous trees (see[9]). Wang has also studied some Shannon-McMillan approximation theorems for arbitrary random field on the generalized Bethe tree (see[10]).

In this paper, we study a class of Shannon-McMillan random approximation theorems for arbitrary random fields on the double rooted tree by comparison the arbitrary measure with the second-order nonhomogeneous Markov measure and constructing a supermartingale on the double rooted tree. As corollaries, a class of Shannon-McMillan theorems for arbitrary random field and second-order Markov chains field on the double rooted tree are obtained. A limit property for the expectation of the random conditional entropy of second-order homogeneous Markov chain indexed by the double rooted tree is studied. Yang and Ye's result (see[13]) is extended.

2. Main result and its proof

Lemma 1 (see [8]). *Let μ_1 and μ_2 be two probability measures defined on (Ω, \mathcal{F}) , $D \in \mathcal{F}$, $\{\tau_n, n \geq 0\}$ be a sequence of positive-valued random variables such that*

$$\liminf_n \frac{\tau_n}{|T^{(n)}|} > 0. \quad \mu_1 - \text{ a.s. } D. \quad (10)$$

Then

$$\limsup_{n \rightarrow \infty} \frac{1}{\tau_n} \log \frac{\mu_2(X^{T^{(n)}})}{\mu_1(X^{T^{(n)}})} \leq 0. \quad \mu_1 - \text{ a.s. } D. \quad (11)$$

In particular, let $\tau_n = |T^{(n)}|$, then

$$\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu_2(X^{T^{(n)}})}{\mu_1(X^{T^{(n)}})} \leq 0. \quad \mu_1 - \text{ a.s. } \quad (12)$$

Proof . See reference [8].

Let

$$\varphi(\mu|\mu_Q) = \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu(X^{T^{(n)}})}{\mu_Q(X^{T^{(n)}})}, \quad (13)$$

$\varphi(\mu|\mu_Q)$ is called the sample relative entropy rate of $X^{T^{(n)}}$ with respect to μ and μ_Q . $\varphi(\mu|\mu_Q)$ is also called asymptotic logarithmic likelihood ratio. By (12) and (13)

$$\varphi(\mu|\mu_Q) \geq \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu(X^{T^{(n)}})}{\mu_Q(X^{T^{(n)}})} \geq 0. \quad \mu - a.s. \quad (14)$$

Hence $\varphi(\mu|\mu_Q)$ can be looked on as a type of a measure of the deviation between the arbitrary random field and the second-order nonhomogeneous Markov chain fields on the double rooted tree.

Although $\varphi(\mu|\mu_Q)$ is not a proper metric between two probability measures, we nevertheless think of it as a measure of "dissimilarity" between their joint distribution μ and second-order Markov distribution μ_Q . Obviously, $\varphi(\mu|\mu_Q) = 0$ if and only if $\mu = \mu_Q$. It has been shown in (14) that $\varphi(\mu|\mu_Q) \geq 0$, a.s. in any case. Hence, $\varphi(\mu|\mu_Q)$ can be used as a random measure of the deviation between the true joint distribution $\mu(x^{T^{(n)}})$ and the second-order Markov distribution $\mu_Q(x^{T^{(n)}})$. Roughly speaking, this deviation may be regarded as the one between coordinate stochastic process $x^{T^{(n)}}$ and the Markov case. The smaller $\varphi(\mu|\mu_Q)$ is, the smaller the deviation is.

Theorem 1. *Let $X = \{X_t, t \in T\}$ be an arbitrary random field on a double rooted tree. $f_n(\omega)$ and $\varphi(\mu|\mu_Q)$ are respectively defined as (7) and (13). Denote by $H_t^Q(X_t|X_{1_t}, X_{2_t})$ the random conditional entropy of X_t relative to X_{1_t}, X_{2_t} on the measure μ_Q , that is*

$$H_t^Q(X_t|X_{1_t}, X_{2_t}) = - \sum_{x_t \in S} Q_t(x_t|X_{1_t}, X_{2_t}) \log Q_t(x_t|X_{1_t}, X_{2_t}), \quad t \in T^{(n)} \setminus \{o, -1\}. \quad (15)$$

Let

$$D(c) = \{\omega : \varphi(\mu|\mu_Q) \leq c\} \quad (16)$$

$$\alpha(c) = \min \left\{ \frac{2xe^{-2}}{(1-x)^2} + \frac{c}{x}, \quad 0 < x < 1 \right\}, \quad c > 0; \quad \alpha(0) = 0. \quad (17)$$

$$\beta(c) = \max \left\{ \frac{2xe^{-2}}{(1+x)^2} + \frac{c}{x}, \quad -1 < x < 0 \right\}, \quad c > 0; \quad \beta(0) = 0. \quad (18)$$

Then

$$\limsup_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t|X_{1_t}, X_{2_t})] \leq \alpha(c)M, \quad \mu - a.s. \quad \omega \in D(c) \quad (19)$$

$$\liminf_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t|X_{1_t}, X_{2_t})] \geq \beta(c)M - c. \quad \mu - a.s. \quad \omega \in D(c) \quad (20)$$

Proof. Consider the probability space $(\Omega, \mathcal{F}, \mu)$, let $\lambda > 0$ be a constant, $\delta_j(\cdot)$ be Kronecker function. Denote $g_t(j) = -\log Q_t(j|X_{1_t}, X_{2_t})$, we construct the following product distribution:

$$\mu_Q(x^{T^{(n)}}; \lambda) = q(x_0, x_{-1}) \prod_{t \in T^{(n)} \setminus \{0, -1\}} \exp\{\lambda g_t(j) \delta_j(x_t)\} \left[\frac{Q_t(x_t|x_{1_t}, x_{2_t})}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \right]. \quad (22)$$

By (22) we can write

$$\begin{aligned} & \sum_{x^{L_n} \in S^{L_n}} \mu_Q(x^{T^{(n)}}; \lambda) \\ &= \sum_{x^{L_n} \in S^{L_n}} q(x_0, x_{-1}) \prod_{t \in T^{(n)} \setminus \{0, -1\}} \exp\{\lambda g_t(j) \delta_j(x_t)\} \left[\frac{Q_t(x_t|x_{1_t}, x_{2_t})}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \right] \\ &= \mu_Q(x^{T^{(n-1)}}; \lambda) \sum_{x^{L_n} \in S^{L_n}} \prod_{t \in L_n} \exp\{\lambda g_t(j) \delta_j(x_t)\} \left[\frac{Q_t(x_t|x_{1_t}, x_{2_t})}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \right] \\ &= \mu_Q(x^{T^{(n-1)}}; \lambda) \prod_{t \in L_n} \sum_{x_t \in S} \exp\{\lambda g_t(j) \delta_j(x_t)\} \left[\frac{Q_t(x_t|x_{1_t}, x_{2_t})}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \right] \\ &= \mu_Q(x^{T^{(n-1)}}; \lambda) \prod_{t \in L_{n-1}} \frac{1}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \left[\sum_{x_t=j} + \sum_{x_t \neq j} \right] \\ &= \mu_Q(x^{T^{(n-1)}}; \lambda) \prod_{t \in L_{n-1}} \frac{e^{\lambda g_t(j)} Q_t(j|x_{1_t}, x_{2_t}) + 1 - Q_t(j|x_{1_t}, x_{2_t})}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|x_{1_t}, x_{2_t})} \\ &= \mu_Q(x^{T^{(n-1)}}; \lambda) \end{aligned} \quad (23)$$

Therefore $\mu_Q(x^{T^{(n)}}; \lambda)$, $n = 1, 2, \dots$ are a class of consistent distributions on $S^{T^{(n)}}$. Let

$$U_n(\lambda, \omega) = \frac{\mu_Q(X^{T^{(n)}}; \lambda)}{\mu(X^{T^{(n)}})} \quad (24)$$

By (22) and (24) we attain

$$\begin{aligned} U_n(\lambda, \omega) &= \exp\left\{ \sum_{t \in T^{(n)} \setminus \{0, -1\}} \lambda g_t(j) \delta_j(X_t) \right\} \prod_{t \in T^{(n)} \setminus \{0, -1\}} \left[\frac{1}{1 + (e^{\lambda g_t(j)} - 1)Q_t(j|X_{1_t}, X_{2_t})} \right] \\ &\quad \cdot q(X_0) \prod_{t \in T^{(n)} \setminus \{0, -1\}} Q_t(X_t|X_{1_t}, X_{2_t}) \Big/ \mu(X^{T^{(n)}}). \end{aligned} \quad (25)$$

It is easy to see that $U_n(\lambda, \omega)$ is a nonnegative sup-martingale from Doob's martingale convergence theorem (see [12]) since μ and μ_Q are two probability measures. Moreover,

$$\lim_{n \rightarrow \infty} U_n(\lambda, \omega) = U_\infty(\lambda, \omega) < \infty. \quad \mu - a.s. \quad (26)$$

By (12) and (24) we have

$$\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log U_n(\lambda, \omega) \leq 0. \quad \mu - a.s. \quad (27)$$

According to (6), (25), we can rewrite (27) as

$$\begin{aligned} & \limsup_{n \rightarrow \infty} \left\{ \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \lambda g_t(j) \delta_j(X_t) \right. \\ & \left. - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log[1 + (e^{\lambda g_t(j)} - 1) Q_t(j|X_{1_t}, X_{2_t})] + \frac{1}{|T^{(n)}|} \log \frac{\mu_Q(X^{T^{(n)}})}{\mu(X^{T^{(n)}})} \right\} \\ & \leq 0 \quad \mu - a.s. \end{aligned} \quad (28)$$

Letting $\lambda = 0$ in (28), we have

$$\varphi(\mu|\mu_Q) \geq \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu(X^{T^{(n)}})}{\mu_Q(X^{T^{(n)}})} \geq 0. \quad \mu - a.s. \quad \omega \in D(c). \quad (29)$$

By use of (16) and (28) we obtain

$$\begin{aligned} & \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \{ \lambda g_t(j) \delta_j(X_t) - \log[1 + (e^{\lambda g_t(j)} - 1) Q_t(j|X_{1_t}, X_{2_t})] \} \\ & \leq \varphi(\mu|\mu_Q) \leq c. \quad \mu - a.s. \quad \omega \in D(c). \end{aligned} \quad (30)$$

By virtue of (30), the properties of super limit and the inequalities $1 - 1/x \leq \ln x \leq x - 1, (x > 0)$, $e^x - 1 - x \leq (1/2)x^2 e^{|x|}$, we can write

$$\begin{aligned} & \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \lambda \{ g_t(j) \delta_j(X_t) - g_t(j) Q_t(j|X_{1_t}, X_{2_t}) \} \\ & \leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \{ \log[1 + (e^{\lambda g_t(j)} - 1) Q_t(j|X_{1_t}, X_{2_t})] - \lambda g_t(j) Q_t(j|X_{1_t}, X_{2_t}) \} + c \\ & \leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} Q_t(j|X_{1_t}, X_{2_t}) [e^{\lambda g_t(j)} - 1 - \lambda g_t(j)] + c \\ & \leq (\lambda^2/2) \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} Q_t(j|X_{1_t}, X_{2_t}) g_t^2(j) e^{|\lambda g_t(j)|} + c \\ & = (\lambda^2/2) \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} Q_t(j|X_{1_t}, X_{2_t}) \log^2 Q_t(j|X_{1_t}, X_{2_t}) e^{-|\lambda| \log Q_t(j|X_{1_t}, X_{2_t})} + c \end{aligned}$$

$$\begin{aligned}
&= (\lambda^2/2) \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log^2 Q_t(j|X_{1_t}, X_{2_t}) \cdot Q_t(j|X_{1_t}, X_{2_t})^{1-|\lambda|} + c. \\
&\quad \mu - a.s. \quad \omega \in D(c)
\end{aligned} \tag{31}$$

In the case $0 < \lambda < 1$, dividing two sides of (31) by λ , we have

$$\begin{aligned}
&\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \\
&\leq \frac{\lambda}{2} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log^2 Q_t(j|X_{1_t}, X_{2_t}) \cdot Q_t(j|X_{1_t}, X_{2_t})^{1-\lambda} + \frac{c}{\lambda} \\
&\quad \mu - a.s. \quad \omega \in D(c)
\end{aligned} \tag{32}$$

Consider the function

$$\phi(x) = (\log x)^2 x^{1-\lambda}, \quad 0 < x \leq 1, \quad 0 < \lambda < 1. \quad (\text{set } \phi(0) = 0) \tag{33}$$

It can be concluded that on the internal $[0, 1]$,

$$\max\{\phi(x), 0 \leq x \leq 1\} = \phi(e^{2/(\lambda-1)}) = \left(\frac{2}{\lambda-1}\right)^2 e^{-2}. \tag{34}$$

By (32) and (34) we have that when $0 < \lambda < 1$,

$$\begin{aligned}
&\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \\
&\leq \frac{\lambda}{2} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \left(\frac{2}{\lambda-1}\right)^2 e^{-2} + \frac{c}{\lambda} \\
&= \frac{2\lambda e^{-2}}{(1-\lambda)^2} \limsup_{n \rightarrow \infty} \frac{|T^{(n)}| - 2}{|T^{(n)}|} + \frac{c}{\lambda} \leq \frac{2\lambda e^{-2}}{(1-\lambda)^2} + \frac{c}{\lambda}. \quad \mu - a.s. \quad \omega \in D(c)
\end{aligned} \tag{35}$$

When $c > 0$, $h(\lambda) = (2\lambda e^{-2})/(1-\lambda)^2 + c/\lambda$ attains its smallest value $\alpha(c)$ at $\lambda_o \in (0, 1)$. Hence letting $\lambda = \lambda_o$ in (35), we attain from (17) that

$$\begin{aligned}
&\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \leq \alpha(c). \\
&\quad \mu - a.s. \quad \omega \in D(c).
\end{aligned} \tag{36}$$

By (7), (6), (15), (29) and (36), noticing $g_t(j) = -\log Q_t(j|X_{1_t}, X_{2_t})$, we can deduce

$$\limsup_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t|X_{1_t}, X_{2_t})]$$

$$\begin{aligned}
&= \limsup_{n \rightarrow \infty} \left\{ -\frac{1}{|T^{(n)}|} \log \mu(X^{T^{(n)}}) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o\}} H_t^Q(X_t | X_{1_t}) \right\} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \{ -\log Q_t(X_t | X_{1_t}, X_{2_t}) - H_t^Q(X_t | X_{1_t}, X_{2_t}) \} \\
&+ \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \left[\sum_{t \in T^{(n)} \setminus \{o, -1\}} \log Q_t(X_t | X_{1_t}, X_{2_t}) - \log \mu(X^{T^{(n)}}) \right] = \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \\
&\sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{j \in S} \{ -\delta_j(X_t) \log Q_t(j | X_{1_t}, X_{2_t}) + Q_t(j | X_{1_t}, X_{2_t}) \log Q_t(j | X_{1_t}, X_{2_t}) \} \\
&\quad + \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu_Q(X^{T^{(n)}})}{\mu(X^{T^{(n)}})} \\
&= \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{j=s_1}^{s_M} [g_t(j) \delta_j(X_t) - g_t(j) Q_t(j | X_{1_t}, X_{2_t})] \\
&\quad + \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu_Q(X^{T^{(n)}})}{\mu(X^{T^{(n)}})} \\
&le \sum_{j=s_1}^{s_M} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j) \delta_j(X_t) - g_t(j) Q_t(j | X_{1_t}, X_{2_t})] \\
&\quad \leq \alpha(c)M \quad \mu - a.s. \quad \omega \in D(c), \tag{37}
\end{aligned}$$

thus in the case $c > 0$, (19) follows from (37).

In the case $-1 < \lambda < 0$, by (31) we have

$$\begin{aligned}
&\liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j) \delta_j(X_t) - g_t(j) Q_t(j | X_{1_t}, X_{2_t})] \\
&\geq \frac{\lambda}{2} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log^2 Q_t(j | X_{1_t}, X_{2_t}) \cdot Q_t(j | X_{1_t}, X_{2_t})^{1+\lambda} + \frac{c}{\lambda}. \\
&\quad \mu - a.s. \quad \omega \in D(c). \tag{38}
\end{aligned}$$

By (34) and (38), we gain

$$\begin{aligned}
&\liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j) \delta_j(X_t) - g_t(j) Q_t(j | X_{1_t}, X_{2_t})] \\
&\geq \frac{\lambda}{2} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \left(\frac{2}{1+\lambda} \right)^2 e^{-2} + \frac{c}{\lambda} \\
&\geq \frac{2\lambda e^{-2}}{(1+\lambda)^2} + \frac{c}{\lambda}.
\end{aligned}$$

$$\mu - a.s. \quad \omega \in D(c). \quad (39)$$

In the case $c > 0$, the function $u(\lambda) = (2\lambda e^{-2})/(1 + \lambda)^2 + c/\lambda$ attains the largest value $\beta(c)$ at $\lambda^o \in (-1, 0)$. Thereby letting $\lambda = \lambda^o$ in (39), we have

$$\liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \geq \beta(c).$$

$$\mu - a.s. \quad \omega \in D(c). \quad (40)$$

By (7), (6), (13), (16) and (40), noticing that $g_t(j) = -\log Q_t(j|X_{1_t}, X_{2_t})$, we can write

$$\begin{aligned} & \liminf_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t|X_{1_t}, X_{2_t})] \\ & \geq \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \{-\log Q_t(X_t|X_{1_t}, X_{2_t}) - H_t^Q(X_t|X_{1_t}, X_{2_t})\} \\ & \quad + \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \left[\sum_{t \in T^{(n)} \setminus \{o, -1\}} \log Q_t(X_t|X_{1_t}, X_{2_t}) - \log \mu(X^{T^{(n)}}) \right] \\ & \geq \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{j=s_1}^{s_M} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \\ & \quad - \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} [\log \mu(X^{T^{(n)}}) - \sum_{t \in T^{(n)} \setminus \{o\}} \log Q_t(X_t|X_{1_t})] \\ & \geq \sum_{j=s_1}^{s_M} \liminf_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] - \varphi(\mu|\mu_Q) \\ & \geq \beta(c)M - c. \quad \mu - a.s. \quad \omega \in D(c). \end{aligned} \quad (41)$$

In accordance with (41), we see that (20) also holds in the case $c > 0$. When $c = 0$, take $0 < \lambda_i < 1, (i = 1, 2, \dots)$ such that $\lambda_i \rightarrow 0$ ($i \rightarrow \infty$), by (35) we acquire

$$\limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} [g_t(j)\delta_j(X_t) - g_t(j)Q_t(j|X_{1_t}, X_{2_t})] \leq 0.$$

$$\mu - a.s. \quad \omega \in D(0). \quad (42)$$

Imitating the proof of (37), we have by (17) and (42)

$$\limsup_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t|X_{1_t}, X_{2_t})] \leq 0. \quad \mu - a.s. \quad \omega \in D(0). \quad (43)$$

Since $\alpha(0) = 0$, we know that (19) also holds in the case $c = 0$ from (37). By the similar means, we can obtain that (20) holds in the case $c = 0$.

Corollary 1. *Under the assumption of Theorem 1, we have that in the case $0 \leq c < 1$,*

$$\limsup_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t | X_{1_t}, X_{2_t})] \leq M \left[\frac{2e^{-2}}{(1 - \sqrt{c})^2} + 1 \right] \sqrt{c},$$

$\mu - a.s. \quad \omega \in D(c)$ (44)

$$\liminf_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t | X_{1_t}, X_{2_t})] \geq -M \left[\frac{2e^{-2}}{(1 - \sqrt{c})^2} + 1 \right] \sqrt{c} - c.$$

$\mu - a.s. \quad \omega \in D(c)$ (45)

Proof. Letting $x = \sqrt{c}$ in (19) and (20), we have

$$[2e^{-2}/(1 - \sqrt{c})^2 + 1] \sqrt{c} \geq \alpha(c), \quad -[2e^{-2}/(1 - \sqrt{c})^2 + 1] \sqrt{c} \leq \beta(c).$$

Therefore (44), (45) follow from (19) and (20), respectively.

Corollary 2. *Under the assumption of Theorem 1, we have*

$$\lim_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t | X_{1_t}, X_{2_t})] = 0. \quad \mu - a.s. \quad \omega \in D(0). \quad (46)$$

Proof. Letting $c = 0$ in Corollary 1, (46) follows from (44) and (45).

Corollary 3. *Let $X = \{X_t, t \in T\}$ be the second-order nonhomogeneous Markov chains field indexed by the double rooted tree with the initial distribution (5) and the joint distribution (6), $f_n(\omega)$ be defined as (8). Then*

$$\lim_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t | X_{1_t}, X_{2_t})] = 0. \quad \mu_Q - a.s. \quad (47)$$

Proof. Let $\mu \equiv \mu_Q$ in Theorem 1, then $\varphi(\mu | \mu_Q) \equiv 0$. Thereby $D(0) = \Omega$. (47) follows from (46) correspondingly.

Remark. When the second-order nonhomogeneous Markov chain indexed by the tree degenerates into the first-order nonhomogeneous Markov chain indexed by a tree, we can see easily that $Q_t(X_t | X_{1_t}, X_{2_t}) = Q_t(X_t | X_{1_t})$, $H_t^Q(X_t | X_{1_t}, X_{2_t}) = H_t^Q(X_t | X_{1_t})$. At the moment, (47) is changed into

$$\lim_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_t^Q(X_t | X_{1_t})] = 0. \quad \mu_Q - a.s.$$

This is a main result of Yang and Ye (see [13]).

3. Shannon-McMillan theorem for homogeneous Markov chains fields on a double rooted tree

Let $X = \{X_t, t \in T\}$ be another second-order homogeneous Markov chain indexed by a double rooted tree with the initial distribution and the joint distribution on the measure μ_P as follows:

$$\mu_P(x_0, x_{-1}) = p(x_0, x_{-1}) \quad (48)$$

$$\mu_P(x^{T^{(n)}}) = p(x_0, x_{-1}) \prod_{t \in T^{(n)} \setminus \{o, -1\}} P(x_t | x_{1_t}, x_{2_t}), \quad n \geq 1, \quad (49)$$

where $P = P(z|x, y)$, $x, y, z \in S$ is a strictly positive stochastic matrix on S^3 , $p = (p(x, y))$ is a strictly positive distribution on S^2 . Thereby the relative entropy density of $X = \{X_t, t \in T\}$ on the measure μ_P is

$$f_n(\omega) = -\frac{1}{|T^{(n)}|} [\log p(X_0, X_{-1}) + \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log P(x_t | x_{1_t}, x_{2_t})]. \quad (50)$$

Let a be a real number, denote $[a]^+ = \max\{a, 0\}$. We have the following result:

Theorem 2. *Let $X = \{X_t, t \in T\}$ be the second-order homogeneous Markov chains field with the initial distribution (48) and joint distribution (49) under the measure μ_P . $f_n(\omega)$ is defined by (50). Let $Q = Q(z|x, y)$, $x, y, z \in S$ be defined by definition 1, $\alpha = \min\{Q(j|i, k), i, k, j \in S\} > 0$. Denote*

$$H_Q(X_t | X_{1_t}, X_{2_t}) = - \sum_{x_t \in S} Q(x_t | X_{1_t}, X_{2_t}) \log Q(x_t | X_{1_t}, X_{2_t}), \quad t \in T^{(n)} \setminus \{o, -1\}.$$

If

$$\sum_{i \in S} \sum_{k \in S} \sum_{j \in S} [P(j|i, k) - Q(j|i, k)]^+ \leq \alpha \cdot c, \quad (51)$$

then

$$\limsup_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_Q(X_t | X_{1_t}, X_{2_t})] \leq \alpha(c)M. \quad \mu_P - a.s. \quad (52)$$

$$\liminf_{n \rightarrow \infty} [f_n(\omega) - \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} H_Q(X_t | X_{1_t}, X_{2_t})] \geq \beta(c)M - c. \quad \mu_P - a.s. \quad (53)$$

Proof. Let $\mu = \mu_P$, $Q_t(z|x, y) \equiv Q(z|x, y)$, $x, y, z \in S$, $t \in T^{(n)} \setminus \{o, -1\}$, we obtain that $H_t^Q(X_t | X_{1_t}, X_{2_t}) = H_Q(X_t | X_{1_t}, X_{2_t})$, $t \in T^{(n)} \setminus \{o, -1\}$, thus (50) follows from (7)

and (49). By the inequalities $\log x \leq x - 1$ ($x > 0$), $a \leq [a]^+$ and (51), noticing that $\alpha = \min\{Q(j|i, k), i, k, j \in S\} > 0$, we can conclude

$$\begin{aligned}
\varphi(\mu_P|\mu_Q) &= \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{\mu_P(X^{T^{(n)}})}{\mu_Q(X^{T^{(n)}})} \\
&= \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{p(X_0, X_{-1}) \prod_{t \in T^{(n)} \setminus \{o, -1\}} P(X_t|X_{1_t}, X_{2_t})}{q(X_0, X_{-1}) \prod_{t \in T^{(n)} \setminus \{o, -1\}} Q(X_t|X_{1_t}, X_{2_t})} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \log \frac{p(X_0, X_{-1})}{q(X_0, X_{-1})} + \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \log \frac{P(X_t|X_{1_t}, X_{2_t})}{Q(X_t|X_{1_t}, X_{2_t})} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \delta_j(X_t) \delta_i(X_{1_t}) \delta_k(X_{2_t}) \log \frac{P(j|i, k)}{Q(j|i, k)} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \delta_j(X_t) \delta_i(X_{1_t}) \delta_k(X_{2_t}) \frac{P(j|i, k) - Q(j|i, k)}{Q(j|i, k)} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \frac{P(j|i, k) - Q(j|i, k)}{Q(j|i, k)} \\
&\leq \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \frac{[P(j|i, k) - Q(j|i, k)]^+}{\alpha} \\
&\leq \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \limsup_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \frac{[P(j|i, k) - Q(j|i, k)]^+}{\alpha} \\
&\leq \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} \limsup_{n \rightarrow \infty} \frac{|T^{(n)}| - 2 [P(j|i, k) - Q(j|i, k)]^+}{|T^{(n)}|} \frac{1}{\alpha} \\
&= \frac{1}{\alpha} \sum_{i \in S} \sum_{k \in S} \sum_{j \in S} [P(j|i, k) - Q(j|i, k)]^+. \tag{54}
\end{aligned}$$

By (51) and (54) we have

$$\varphi(\mu_P|\mu_Q) \leq c. \quad a.s. \tag{55}$$

By (16) and (55) we know $D(c) = \Omega$. Hence (52), (53) follow from (19), (20), respectively.

Theorem 3. *Let $X = \{X_t, t \in T\}$ be a second-order homogeneous Markov chains field indexed by the double rooted tree with the initial distribution (1) and the transition matrix $Q = Q(z|x, y)$, $x, y, z \in S$. Then*

$$\lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} E_Q[H_Q(X_t|X_{1_t}, X_{2_t})] = - \sum_{i \in S} \sum_{j \in S} \sum_{k \in S} q(i, j) Q(k|i, j) \log Q(k|i, j),$$

$$\mu_Q - a.s., \quad (56)$$

where E_Q represents the expectation under the measure μ_Q .

Proof. By the definition of $H_Q(X_t|X_{1_t}, X_{2_t})$ in Theorem 2 and the property of the conditional expectation, we can write

$$\begin{aligned}
& \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} E_Q[H_Q(X_t|X_{1_t}, X_{2_t})] \\
= & \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} E_Q[E_Q(-\log Q(X_t|X_{1_t}, X_{2_t})|X_{1_t}, X_{2_t})] \\
= & \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} E_Q(-\log Q(X_t|X_{1_t}, X_{2_t})) \\
= & \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{x_{1_t} \in S} \sum_{x_{2_t} \in S} \sum_{x_t \in S} [-q(x_{1_t}, x_{2_t}, x_t) \log Q(x_t|x_{1_t}, x_{2_t})] \\
= & \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{j \in S} \sum_{k \in S} [-q(i, j, k) \log Q(k|i, j)] \\
= & \lim_{n \rightarrow \infty} \frac{1}{|T^{(n)}|} \sum_{t \in T^{(n)} \setminus \{o, -1\}} \sum_{i \in S} \sum_{j \in S} \sum_{k \in S} [-q(i, j)Q(k|i, j) \log Q(k|i, j)] \\
= & \sum_{i \in S} \sum_{j \in S} \sum_{k \in S} [-q(i, j)Q(k|i, j) \log Q(k|i, j)] \cdot \lim_{n \rightarrow \infty} \frac{|T^{(n)}| - 2}{|T^{(n)}|} \\
= & \sum_{i \in S} \sum_{j \in S} \sum_{k \in S} [-q(i, j)Q(k|i, j) \log Q(k|i, j)]. \quad (57)
\end{aligned}$$

Therefore, (56) follows from (57) directly.

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